OPTIMIZATION OF HYDRAULIC PROCESSES IN OPEN CHANNELS BASED ON DEEP LEARNING MODELS

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K E Y W O R D S

open channel, hydraulic processes, DeeP Learning, LSTM, water resources management

A B S T R A C T

Under conditions of water resource scarcity and climate change, the issue of efficient water management in irrigation systems is becoming increasingly important. Accurate prediction of hydraulic processes in open channels is complex due to the nonlinear behavior of these systems and hydraulic inertia. In this study, a data-driven approach based on a Long Short-Term Memory (LSTM) neural network is proposed for predicting water discharge in open channels. The Mirishkor irrigation canal in the Republic of Uzbekistan was selected as the research object. The model was trained using time-series data of water level, gate opening degree, and inflow discharge. A dataset reflecting the channel dynamics was generated by considering time delay and inertia. According to the experimental results, the linear regression model failed to represent the system dynamics ($R^2 = 0.0039$), whereas the LSTM model demonstrated high accuracy ($R^2 = 0.7963$). The RMSE and MAE indicators decreased by 54% and 55%, respectively. The results show that sequence-based neural networks are effective in modeling open channel systems. The obtained findings confirm that deep learning models are an effective tool for developing optimal control and decision-making systems in open channels.

INTRODUCTION

Under conditions of limited water resources and climate change, the need to transition from traditional irrigation systems to smart and digital water management systems is steadily increasing. Open channels represent a key component of water supply in agriculture, and their efficient operation directly affects crop productivity. However, water movement in open channels has a dynamic nature and produces delay and inertia depending on variations in water level, gate opening degree, and inflow discharge, which complicates the control process.

Although statistical methods such as linear regression are simple and fast, they cannot adequately represent long-term temporal dependencies and hydraulic inertia. Irrigation canals in the Kashkadarya region of Uzbekistan are of vital importance for agriculture; however, due to the complexity of their hydraulic regime, difficulties arise in accurate water distribution [2]. The main problem in predicting water discharge in large irrigation systems such as the Mirishkor canal is **hydraulic inertia**. In other words, when a gate is opened in the upstream section of the canal, its effect reaches the downstream section after a certain time delay. Conventional statistical methods (linear regression) cannot account for this temporal dependency, which results in water losses; moreover, the traditional Saint-Venant equations are computationally complex for real-time calculations [5].

As noted by Kamyab et al. (2023) [1], big data analysis and artificial intelligence (AI) provide revolutionary opportunities for water resource conservation. Advances in the field of deep learning, particularly recurrent neural

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networks and LSTM architectures, have demonstrated high performance in modeling hydrological and hydraulic processes. In many studies, LSTM models have been applied to predict river flow and water levels. However, most existing works focus on natural rivers, while studies that consider hydraulic inertia and time delays in large irrigation canals controlled by gates remain limited.

The main objective of this study is to develop an LSTM model for predicting hydraulic processes in open channels using the Mirishkor canal as a case study and to quantitatively compare its performance with a classical linear regression model.

METHODS

Mathematical Model of Canal Dynamics

In an open channel hydraulic system, the output water discharge depends not only on current parameters but also on previous time values. This phenomenon is explained by inertia and time delay.

The channel dynamics can be expressed by the following generalized discrete equation[8]:

$$Q_{out}(t) = \alpha Q_{out}(t-1) + \beta Q_{in}(t-d) + \gamma H(t) + \delta S(t) + \varepsilon_t \quad (1)$$

Where:

$Q_{out}(t-1)$ - hydraulic inertia component
$Q_{in}(t-d)$ - time delay of *d* days
α - inertia coefficient
β - coefficient of delay influence
ε_t - random disturbance

This equation reflects the real dynamic characteristics of an open channel.

Linear Regression Model (LR)

In order to evaluate the effectiveness of the proposed Deep Learning approach, despite the dynamic equation presented above, a classical **Linear Regression (LR)** model was developed in this study as a baseline comparison model. Linear regression is statistically simple and computationally efficient, and it is often used in hydraulic systems to approximately estimate the relationship between water discharge and the factors influencing it.

In this work, the linear regression model was applied to predict the output water discharge based on the current hydraulic state of the open channel. The input variables of the model were selected as water level $H(t)$, gate opening degree $S(t)$, and inflow water discharge $Q_{in}(t)$, while the output variable was considered as the outflow water discharge $Q_{out}(t)$.

The mathematical expression of the linear regression model can be written as follows:

$$\hat{Q}_{out}(t) = \beta_0 + \beta_1 H(t) + \beta_2 S(t) + \beta_3 Q_{in}(t) \quad (2)$$

Where:

$\hat{Q}_{out}(t)$ - predicted outflow water discharge generated by the model;
β_0 - intercept (bias), representing the average baseline level of the system;
β_1 - coefficient representing the effect of water level on the outflow discharge;
β_2 - coefficient representing the effect of gate opening;
β_3 - coefficient representing the effect of inflow water discharge.

These coefficients are determined using statistical estimation methods, specifically based on the **Least Squares** method. Parameter estimation is performed by solving the following optimization problem:

$$\min \sum_{t=1}^{N} \left(Q_{out}(t) - \hat{Q}_{out}(t) \right)^2 \quad (3)$$

Where:

$Q_{out}(t)$ - actual observed value;
$\hat{Q}_{out}(t)$ - value calculated by the model;
n - number of observations.

This function aims to minimize the sum of squared errors between the actual and predicted

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values. An important point is that the linear regression model considers only the parameters at the current time. It does not take into account dynamic components such as $Q_{out}(t-1)$, $Q_{in}(t-d)$ hydraulic inertia (the previous value of the outflow discharge) and time delay (the delayed effect of inflow discharge). Therefore, this model has a static nature and cannot fully represent the temporal dynamic processes in an open channel system.

The linear regression model was implemented in the Python programming language using the scikit-learn library. Since the data had a time-series structure, shuffling was not performed when splitting the dataset into training (80%) and testing (20%) sets. As a result, the model was trained on 292 days of data and evaluated on 73 days of independent test data.

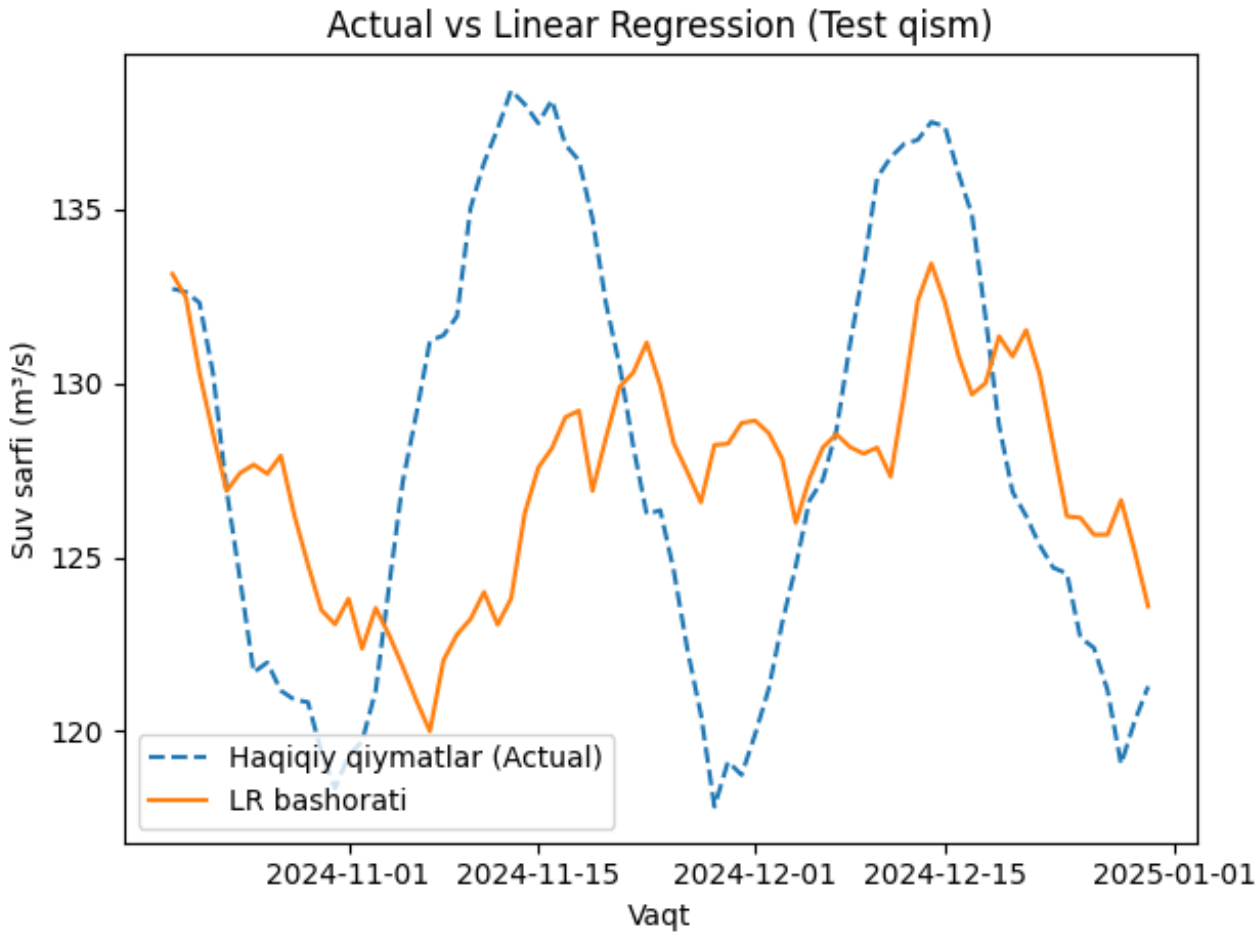


Figure 1. Comparison of the actual outflow water discharge and the outflow water discharge predicted using the linear regression model.

The predictive performance of the model was evaluated using the Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). According to the obtained results, the following values were observed for the linear regression model on the test dataset: RMSE = 6.4315, MAE = 5.4160, and R^2 = 0.0039. Although these indicators show that the model represents the general trend relatively well, it fails to adequately capture sudden changes in water flow and temporal delays.

This situation reveals the main limitation of the linear regression model: the model considers only the hydraulic parameters at the current time moment and cannot model the hydraulic inertia and temporal dependencies inherent in canal systems. Therefore, in this study, the results obtained from the linear regression model were taken as a baseline for comparison with the results of the deep learning–based LSTM model.

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Prediction Based on the Long Short-Term Memory (LSTM) Model

Although the linear regression model makes it possible to estimate the general trend of water discharge in open channels, it cannot adequately represent the hydraulic inertia and temporal delays inherent in canal systems. Therefore, in this study, a model based on a **Long Short-Term Memory (LSTM)** neural network, which allows consideration of long-term dependencies in time-series data, was proposed[4].

The LSTM model is an advanced type of recurrent neural network that overcomes the "vanishing memory" problem found in conventional recurrent networks by using a special cell state and control gates. This property enables the LSTM model to mathematically represent the delayed influence of water flow in open channels over time.

Stages of the method operation:

- Data collection (H, S, Q).
- Conversion of data into a time-series sequence.
- Learning nonlinear hydraulic relationships through **LSTM layers**.
- Control of the gates based on the obtained results.

Structure of the LSTM model

The LSTM neural network is based on powerful and complex mathematical formulations. Its main difference from conventional neural networks is that it has a special system of "gates" that control the storage, deletion, and updating of information [3].

The LSTM model operates with sequential data. The input data were provided in the following windowed format:

$$X_t = \{x(t-L+1), ..., x(t)\}$$

where L = 21 and

$$x(t) = \left[H(t), S(t), Q_{in}(t)\right]$$

In this study, the LSTM model receives as input the sequential time-step values of water level $H(t)$, gate opening degree $S(t)$, and inflow water discharge $Q_{in}(t)$. The output of the model is the predicted outflow water discharge $Q_{out}(t)$, taking into account a certain time delay.

The computations of the LSTM at each step (at time t) are performed using the following mathematical formulas:

Forget Gate

The calculations of the LSTM model at each time step are expressed through the following fundamental equations. First, the forget gate determines the extent to which the information stored in the previous memory should be retained:

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f) \quad (4)$$

— f_t - Forget coefficient (a value between 0 and 1). Its function is to determine which part of the previous memory C_{t-1} has become outdated. For example, if the water released into the canal 10 days ago has a reduced influence on the current flow, the model discards that information.

— σ - Sigmoid function, a nonlinear operator that regulates the flow of information.

— W_f - Weight coefficients of the forget gate (parameters learned by the model).

— h_{t-1}- Output result from the previous time step.

— x_t - Vector of hydraulic input parameters at the current time step, which includes:

- H_t - water level
- S_t - gate position
- Q_{in} - inflow water discharge

— b_f - Bias term of the forget gate.

Here, t represents the current time step (for example, today), while $t-1$ represents the previous time step (for example, yesterday). The function σ - maps values into the interval [0, 1], where 0 means "completely forgotten" and 1 means "fully retained". The parameter b is an additional coefficient that increases the model's flexibility [7].

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2. Input Gate

The input gate determines how much of the newly arriving hydraulic information (for example, the new opening degree of the gate) should be stored in memory.

$$i_t = \sigma(W_i * [h_{t-1}, x_t + b_i]) \qquad (5)$$

$$\tilde{C}_t = \tanh(W_C * [h_{t-1}, x_t] + b_C) \quad (6)$$

— i_t - Degree of acceptance of new information. Its function is to determine which part of the incoming data (x_t) should be written into memory. For example, it decides how much of the newly observed gate opening (in centimeters) should be incorporated into the system's internal state. Yangi ma'lumotlarni qabul qilish darajasi.

— $\tilde{C}_t$ - Candidate memory state for the current time step, representing the new hydraulic condition that may be added to memory. It represents the block of new information that can be stored.

— tanh - Hyperbolic tangent (tanh) function, which stabilizes values within the range [-1, 1]. It transforms data into a bounded interval and regulates the information flow.

— W_i, W_C - Weight matrices for the input gate and candidate state.

— b_i, b_C - Bias terms for the input gate.

3. Cell State (Memory State)

The update of the memory cell is performed as follows:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \qquad (7)$$

— C_t - current cell state (overall memory at the current time step, representing today's hydraulic condition of the channel). This is the core component of the LSTM, responsible for long-term information storage.

— C_{t-1} - previous cell state (memory from the previous time step, representing yesterday's channel inertia).

— $f_t * C_{t-1}$ - retained portion of the old information after applying the forget mechanism.

— $i_t * \tilde{C}_t$ - proportion of newly added hydraulic information incorporated into the memory state.

4. Output Gate

The output gate forms the final prediction (water discharge) based on the information stored in memory.[9]

$$o_t = \sigma(W_o * [h_{t-1}, x_t] - b_o) \quad (8)$$

$$h_t = o_t * \tanh(C_t) \qquad (9)$$

— o_t - Output gate coefficient. It determines which part of the memory should be exposed as output (prediction).

— h_t - Final output of the model (predicted Q water discharge for the tested channel).

— W_o, b_o - Weights and bias terms of the output gate, respectively.

Based on this hidden state, the outflow water discharge is predicted as follows:

$$\hat{Q}_{out}(t) = W_y h_t + b_y \quad (10)$$

All weight coefficients and bias terms of the LSTM model were learned by minimizing the squared error between the actual outflow water discharge $Q_{out}(t)$ and the predicted values $\hat{Q}_{out}(t)$ on the training dataset. The model was implemented in the Python programming language using the TensorFlow/Keras libraries.

This system of equations mathematically models the **time delay** of the water wave propagation from upstream to downstream in channel hydraulics. Unlike simple statistical models, the presence of the C_t **(memory)** component links the past state of the channel to the current prediction. Each parameter W and b adapts during the training process to the real hydraulic resistance and slope characteristics of the canal.

RESULTS AND DISCUSSION

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To evaluate the performance of the proposed Deep Learning–based LSTM model, it was quantitatively compared with the classical Linear Regression (LR) model in this study. Both models were tested using the same training (80%) and testing (20%) datasets. The evaluation was performed using the coefficient of determination R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) metrics.

In the linear regression model, the outflow water discharge was predicted using the relationship given in (2). The model parameters were determined by minimizing the squared error between the actual outflow water discharge $Q_{out}(t)$ and the predicted values $\hat{Q}_{out}(t)$. This approach shows that the linear regression model considers only the hydraulic state at the current time step.

In contrast, the LSTM model predicts the outflow water discharge not only based on *t* at time t, but also considering the hydraulic states of the previous time steps. The main computations of the LSTM model are expressed through the following equations:

- First, the forget gate determines how much of the previous memory state should be retained using equation (4).
- The input gate determines how much of the newly arriving information should be written into memory through equations (5) and (6).
- The cell state (memory) is updated through equation (7).
- The output gate determines the hidden state based on equations (8) and (9).
- Finally, the predicted outflow water discharge of the LSTM model is obtained using equation (10).

The prediction accuracy of both models was evaluated using the following metrics.

Mean Absolute Error (MAE):

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|Q_{out}(t) - \hat{Q}_{out}(t)\right| \qquad (11)$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(Q_{out}(t) - \hat{Q}_{out}(t))^2} \qquad (12)$$

Root Mean Square Error (RMSE):

$$R^2 = 1 - \frac{\sum_{t=1}^{N}\left(Q_{out}(t) - \hat{Q}_{out}(t)\right)^2}{\sum_{t=1}^{N}\left(Q_{out}(t) - \bar{Q}_{out}\right)^2} \qquad (13)$$

Here:

N – number of test samples;;

$\bar{Q}_{out}$ – average value of the actual output water discharge.

Table 1:

Comparative analysis of model performance.

Metric	Simple method (LR)	Proposed method (LSTM)	Difference (Effect)
R^2 (Accuracy)	0.0039	0.7963	≈79% higher
MAE (Error)	5.4160	2.4310	≈55 % reduction
RMSE (Squared Error)	6.4315	2.9577	≈54 % reduction
Time inertia consideration	Not considered	Fully considered	-

The obtained results showed that although the linear regression model represented the general trend relatively well, it was not able to adequately capture sudden changes in water flow and time-delay effects. The LSTM model, on the other hand, significantly improved prediction accuracy by considering the previous hydraulic states of the canal through its memory mechanism. In particular, the sharp decrease in the RMSE value clearly demonstrated the LSTM model's ability to effectively model hydraulic inertia in open channels.

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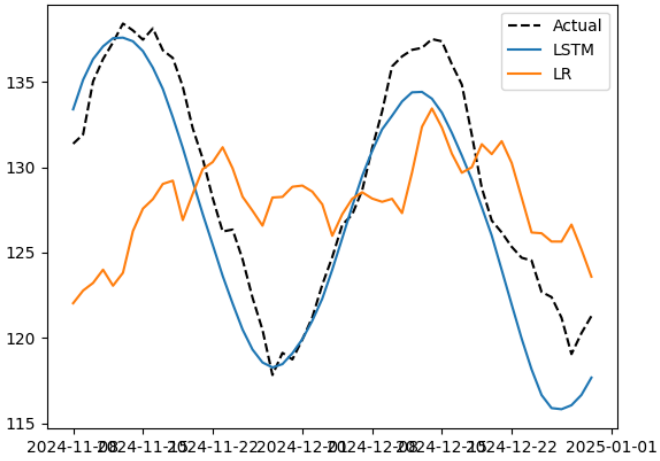


Figure 2. *Graphical analysis of water discharge prediction obtained using the LSTM model developed in Python and the conventional (Linear Regression) model*

The model was developed using the TensorFlow/Keras libraries of the Python programming language. After the training process, the following statistical indicators were obtained [6]:

CONCLUSION

Determining optimal water distribution in canal systems is an important research direction for the rational and efficient allocation of water resources in agricultural irrigation areas. The conducted study shows that simple statistical methods are not sufficient for predicting water discharge in canals with complex hydraulic systems. This study demonstrated the high efficiency of deep learning methods in modeling and predicting hydraulic processes in open irrigation canals. The proposed LSTM model has significantly higher accuracy compared to the classical linear regression model and considerably reduces prediction errors in water discharge forecasting. The obtained results serve as a strong scientific basis for optimizing water distribution in open channels, real-time control, and the development of intelligent decision-making systems. In future, it is planned to integrate this model with real control algorithms and apply it in other irrigation networks.

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